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ORIGINAL PAPER

Resource selection of moose (*Alces alces cameloides*) and their response to human disturbances in the northwestern slope of Lesser Khingan Mountains, northeastern China

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Abstract: Moose (*Alces alces cameloides*) is typically representative of the fauna of the frigid temperate zone and has been put on the Chinese second priority list of protected animals. The moose of northeast China is on the southern most edge of its distribution in Asia. To study resource selection characteristics of moose and their response to human disturbances and forest resource variables, the field work was conducted in Heilongjiang Provincial Shengshan Forestry Farm, which is located in the northwestern slope of Lesser Khingan Mountains, northeastern China, from January to March in both 2006 and 2007. A total of 428 plots were examined within the study area. Signs of moose use were found in 19 plots. Based on the analysis of resource selection function, we found that moose selected areas with higher densities of mixed deciduous broadleaf patch and mixed coniferous and broad leaf patch, and a higher NDVI value. Moose avoided settlement 6 km away and remained low probability of occurrence within 3 km from roads, whereas higher within 4 km from trails. Our results suggested that the behavior of avoidance for human disturbance (i.e. settlement and roads) may indirectly pose habitat loss. Therefore, resource selection function models and corresponding graphs of important habitat disturbances can be used to guide and evaluate future development plans.

Key words: *Alces alces cameloides*; human disturbances; resource selection function; Kappa statistic

Introduction

Moose (*Alces alces cameloides*) is typically representative of the fauna of the frigid-temperate zone. In China, it is distributed only in the Greater Khingan Mountains and part of the Lesser Khingan Mountains. China lies on the southernmost edge of Moose's distribution area in Asia. In recent years, both the area of distribution and the population of moose in China have been declining as a result of disturbance from anthropogenic factors; therefore, the moose has been put on the Chinese second priority list of protected animals (Wang 1998). Historically, moose were ubiquitous throughout the Greater Khingan Mountains and part of the Lesser Khingan Mountains. A survey in the 1970s estimated the total Chinese population of moose to be 18,538 individuals (Ma 1989). In 1987, another census showed a population of about 10,000 individuals, with about 6,000 individuals in the Greater Khingan Mountains and about 3,000 individuals in the Lesser Khingan Mountains, and the average density was 0.0519 individuals/km^2. Hence, in 17 years, its population decreased by 46.2% at an annual decline rate of 6.3%. Its area of geographic distribution, which initially was 190,000 km^2, shrank toward north and west by nearly 100–200 km, resulting in lost habitat of 55,102 km^2 accounting for 21.6% of its historical distribution. At the present situation, its population size and distribution may still be in decline (Piao et al. 1995).

The moose is the largest member of the deer family in body size and has no natural predator within the study area (Yu et al. 1993). However, human impacts pervade most ecosystems in northeastern China. The over exploitation of forests for timber production,

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the expansion of rural and suburban housing, and tourism has resulted in a greater presence of people across areas that were once exclusively habitats for moose. The impacts may result in a direct loss of habitat, but there may also be indirect loss of habitat as a consequence of avoidance behavior by affected wildlife (Mace and Waller 1996; Stevens and Boness 2003). These human disturbances have led to the identification of habitat degradation as a potential threat to the species.

A detailed understanding of habitat selection for moose is required to address the impact of habitat factors on the moose including human disturbances. In addition, landscape structure has important impacts on spatial distribution of a population (Stenseth 1980; Dempster and Pollard 1986; Dunning et al. 1992). Also, consideration of multi-scale variables is necessary for deciding how habitat data should be applied in resource management. It has been argued that abiotic factors of the environment are primary determinants of broad-scale distribution patterns for large herbivores (Bailey et al. 1996; Fortin et al. 2003). The purpose of our study was to better understand the influence of vegetation and human disturbance on the distribution of moose.

Materials and methods

Study area

The study was conducted at Heilongjiang Provincial Shengshan Forestry Farm (49°24′–49°35′N, 126°27′–126°55′E), located in the northwestern slope of Lesser Khingan Mountains, northeastern China, covering 155.6 km^2.

The forest farm is located in the lower elevations of the mountains at average altitude of 450 m, with undulating terrain in relative height of 100–200 m, with average slopes of l0°. The weather is characterized by long cold winters and short hot summers. The annual average temperature is -2°C, and extreme temperatures range from -38.8°C to 34.3°C. Average annual precipitation ranges from 500 to 700 mm. The frost-free period is 100–120 days lasting from late April to late September. The vegetation flourishes and provides good cover for wildlife. In addition, a comprehensive drainage system merges to form a large area of wetland within the study site. Other ungulates in this forest region include roe deer (*Capreolus pygargus bedfordi*) and wild boar (*Sus scrofa ussuricus*). The only carnivorous species is the lynx (*Lynx lynx*), but it is extremely rare in our study area. There is only one village in the forest farm. A relatively sparse network of functioning roads and trails is associated with forestry operations.

Collection of resource and human disturbance variables

Field work was conducted 24 hours after snowfall from January to March in both 2006 and 2007. A total of 428 10 m × 10 m plots were placed every 200 m to avoid clustering along 28 sampling transects. Twenty eight transects, each more than 2 km in length, were located by randomly selecting the starting point of the first transect and extending that transect 2 km to the south. The remaining transects were established in an approximately parallel array at 2-km intervals extending to the west, traversing the whole study area and covering all habitat types (Fig. 1). The GPS location at the center of each 10 m × 10 m plot was recorded. At each plot, we firstly examined the presence of moose and roe deer by identifying fresh snow tracks (left within 24 hours), beds, dung pellet (Chang and Xiao 1988; Zhang and Xiao 1990; Lennart 2002; Jiang et al. 2006), and then recorded or generated some habitat variable data at patch or landscape variables (Table 1).

Vegetation types were determined by remote sensing. Digital forest cover and land use maps were generated by visual interpretation of Spot-5 imagery (resolution: 2.5 × 2.5 m, Volume: Network YZP0016533) taken on September 21, 2005. Aerial photographs were used to build more sensitive photo mosaics for classification of vegetation type. Photographs were scanned and mosaics rectified with remote sensing software (ERDAS Inc. ERDAS IMAGINE 8.5 Tour Guides 2001) and then digitized using Arc View GIS Version 3.1 (ESRI Inc.1996). Classification of vegetation types was primarily based on categories established by the Zhanhe Forest Bureau Forestry Management Map (2002). Five forest stands were identified using an unsupervised classification with an iterative self-organizing data analysis technique and a supervised classification based on expert knowledge gained in the field (ERDAS Inc. IMAGINE Subpixel-Classifier 8.5 User Guides 2001). The five cover types were *Betula platyphylla* stands, mixed deciduous broadleaf forest stands, *Larix gmelinii* forest stands, mixed coniferous and broad leaf forest stands, and low shrub and swamp.

We defined a vegetation patch as a single or homogeneous collection of pixels representing one cover type. We queried the percentage use of each cover type found across the study area. And then, we generated a second set of variables quantifying the density of patches representing the landscape variation in the availability of each cover type across the study area (Johnson et al. 2004). We used a pattern analysis technique, 3-term local quadrat variance, to identify the distributional patterns of each land cover type. First, we randomly placed 10 north-to-south transects across each cover type. We then used an overlapping moving window, consisting of three terms or blocks, to calculate the variance in pixel (i.e. patch) occurrence along each transect. The variance was repeatedly calculated for each transect following incremental increases in block size. When plotted, peaks in variance corresponding with block size indicate patchiness (Dale 2000). We plotted the median variance for the 10 sample transects and identified the major peak in variance as one variable at which the broader-scale analysis of the vegetation differed beyond that of the individual patches (Johnson et al. 2004). We used that scale (i.e. distance) to identify the size of a rectangular moving window that was applied to a binary image of each land cover type to calculate and map the density of pixels (i.e. patches) across the study area. These analyses were conducted at a pixel resolution of 100 × 100 m.

The altitude was derived from a Digital Elevation Model (DEM) for the study area by using ArcView GIS Version 3.1 (ESRI Inc., 1996). The Sun index were calculated by the equation: cos(aspect) × tan (slope) ×100 (Wilson et al. 2001). Slope and aspect were generated using a digital elevation model (DEM). Viewshed was

generated from an elevation surface (TIN-Triangulated Irregular Network) with, for each plot, the number of hypothetical observers (one in the centre of each of the other plots) who can see the position. The result is a grid theme with visibility attributes assigned to every cell (plot) (Maichak 2004). A Normalized Difference Vegetation Index (NDVI) was derived from 21 September 2005 SPOT 5 imagery by using remote sensing software (ERDAS Inc., 2001). Greenness, wetness and brightness were produced using a tasseled cap image transformation (Crist and Ciscone 1984) from the 2005 Spot 5 image.

Table 1. Variables used to model resource selection by moose, in Shengshan Forest Farm of northwestern slope of Lesser Khingan Mountains, northeastern China (January to March 2006 and January to March 2007).

Variable	Description	Abbreviation
Resource Variables[a]		
Betula platyphylla patch/density	*Betula platyphylla* accounts for more than 80 percent of arboreal forest stands	BET-P/D
Mixed deciduous broadleaf patch /density	*Betula platyphylla* dominated and mixed with *Populus* spp., *Salix* spp., *Alnus incana*, *Quercus mongolica*, *Tilia* spp.etc. deciduous arboreal forest stands	MDB- P/D
Larix gmelinii patch /density	*Larix gmelinii* account for more than 80 percent of arboreal forest stands	LAR-P/D
Mixed coniferous and broad leaf patch /density	*Betula platyphylla*, *Populus* spp., mixed *Larix gmelinii*, *Picea koraiensis*, *Abies sibirica* etc. coniferous and broad leaf stands	MCB-P/D
Low shrub and swamp patch /density	Shrub (*Corylus* spp., *Rhododendron dahuricum*, *Betula fruticosa* etc. between 0 and 2m high) and wetland	LSS-P/D
Normalized difference vegetation index	Measure of the proportion of photosynthetically absorbed radiation	NDVI
Greenness	Measure of reflectance of green vegetation (Crist and Cicone 1984)	GREEN
Brightness	Measure of reflectance of green vegetation (Crist and Cicone 1984)	BRIGHT
Wetness	Measure of soil moisture (Crist and Cicone 1984)	WET
Altitude	Generated from a digital elevation model	ALT
Sun index	Slope and aspect generated from a digital elevation model according to the equation: cos (aspect)×tan (slope)×100 (Wilson *et al*. 2001,2003)	SUN
Viewshed	Viewshed analysis indicates not only what areas of a surface can be seen by one or more observers, but also, for any visible position, how many observers can see the position (ArcView 3.1) (Jiang et al. 2009).	VIEW
Distance to river	Distance to the closest pixel of river from a given location	DRIVER
Occurrence of roe deer	Predicted likelihood of encountering roe deer by using RSF (The method is the similar to that of Jiang et al. 2010)	OROE
Human Disturbance Factors		
Distance to settlement	Distance to the closest pixel of settlement	DSETTLE
Distance to roads	Distance to the closest pixel of roads	DROAD
Distance to trails	Distance to the closest pixel of trails(or abandoned roads)	DTRAIL
Forest harvest interval	The time interval to the most recent forest harvest in a given location	FHIN

[a]: Vegetation was modeled at two scale variables: percent area per type and mean density representative of the regional distribution of each vegetation type

Viewshed analysis determines areas visible and not visible on a grid or triangulated irregular network (Wang et al. 1996) from one (e.g. a sample site) to many observation sites. Results are stored as a temporary integer grid where the value of each cell in the grid equals the number of sites from which it can be seen (Ormsby and Alvi 1999). For example, cells with a value of 1, 2 and 3 can be seen from one, two and three observation sites, respectively. Cells with a value of 0 can not be seen from any observation site. Therefore, the higher Viewshed value a site has, the easier the site can be seen and the poorer its usefulness for concealment in the terrain. We calculate the Viewshed index of all survey plots by using a software application within the 3D extension (Ormsby and Alvi 1999) of ArcView GIS 3.1.

We hypothesized that the distribution of roe deer was correlated with the availability of moose and that the movement and behavior of moose was influenced by the presence of roe deer (Li et al. 1992). Therefore, we firstly modeled and generated maps of habitat selection for roe deer. This map, in turn, then provided spatially explicit covariates to evaluate the strength of interspecific interactions between roe deer and moose. Thus we can use occurrence of roe deer to infer interactions with moose (Johnson et al. 2005).

Spatial distances (i.e. the distance to nearest settlement, roads, trails, rivers), slope degree and aspect were measured by the spatial analysis model provided in ArcView 3.1. In addition, forest harvest interval was quantified by the interval between the present and the time of the most recent forest harvest at a given location, and we converted these logged locations into a grid surface by using ArcView 3.1 (ESRI Inc.1996).

Creation of resource selection function models

We used resource selection functions (RSF) to quantify the relationship between the observed distribution of moose and the

variables representing habitat characteristics and human disturbance. A RSF is any mathematical function that is proportional to the probability of use of a resource or habitat (Manly et al. 2002). Typically, a RSF consists of several coefficients (β_i) that quantify selection for or avoidance of some environmental features. Coefficient sign and strength are results of differential variation in the distribution of each environmental feature measured at a sample of animal locations and a comparable set of absence sites. Habitat variables were tested for normality using Kolmogorov-Smirnov and Shapiro-Wilk tests. Some variables were highly skewed and needed to be normalized using standard transformation techniques. All variables were subsequently entered into a Pearson's correlation matrix to identify collinearities between significant variables (i.e. $r_s \geq 0.65$) (Loyn et al. 2001). Variables that had collinearities were examined and the variable that explained a greater portion of the deviance was retained. All significant variables were then entered into the model development procedure. We used an information-theoretic approach to guide model development and selection (Anderson et al. 2000). We used the Akaike Information Criterion (AIC_C) difference adjusted for small sample size and Akaike weights (w) to evaluate and choose the most parsimonious model (i.e., the fewest variables to explain the greatest amount of variation). Akaike weights provide a normalized comparative score for all specified models and are interpreted as the approximate probability that each model is the best from the set of proposed models (Anderson et al. 2000).

Following selection of the most parsimonious of the habitat selection models, we evaluated all combinations of terms for the disturbance covariates. Our work was premised on avoidance as the indicator of disturbance. Although we are confident that observed patterns of avoidance are a proxy for a real effect, we recognize the limitations of our data and the possibility of false negatives. Holding modeled disturbance effects constant and applying predetermined coefficients allowed us to easily assess the simple "footprint" impacts associated with current roads, trails, and the settlement. Similar approaches were used to assess the impacts of human actions on the availability of habitats for grizzly bears (Schoen et al. 1994; Dixon 1997; Suring et al. 1998; Jiang et al. 2007). Consequently we required the final model to have a relative low AIC_C and may select a convex Gaussian disturbance term indicative of avoidance of a disturbance feature (i.e., nonlinear variables).

We used 95% confidence intervals to assess the strength of effect of each predictor covariate. Selection or avoidance cannot be inferred from covariates whose confidence intervals include 0. We used the Pregibon's $\Delta\beta$ and leverage statistics and Hosmer and Lemeshow's $\Delta\chi^2$ statistic to identify cases and clusters that had a large influence on the parameters of the model (Hosmer and Lemeshow, 2000). Predictions generated from an RSF are relative measures of habitat selection, not true probabilities of the occurrence of particular behaviors. Therefore, we used the odds ratio as a relative measure of habitat selection (Menard 2001; Keating and Cherry 2004).

$$\text{Odds ratio} = \exp(\beta_1\chi_1 + \beta_2\chi_2 + \ldots + \beta_i\chi_i) \quad \text{(eq. 1)}$$

We populated Equation 1 with coefficients ($\beta_1, \beta_2 \ldots \beta_i$) from regression models.

Here, we assumed that our definition of availability was functionally related to an animal's response to human disturbance.

The AIC_C provides evidence for selection of the most parsimonious model, but does not permit evaluation of discriminatory performance (Pearce and Ferrier 2000). We use Kappa statistic for evaluating classification effectiveness of a model. Kappa records overall agreement between predictions and observations, corrected for agreement expected to occur by chance. The statistic ranges from -1 to +1, where +1 indicates perfect agreement while values of zero or less suggest a performance no better than random (Cohen 1960). Important advantages of Kappa are the use of agreement, instead of association (traditional classification tables). This is particularly important when the prevalence of the species is low (Fielding and Bell 1997), a frequent phenomenon in wildlife RSF modeling because models often are developed for rare, threatened, or endangered species.

We completed the creation of logistic models and Kappa statistic evaluation using R2.4.1, a statistical data analysis program (R Development Core Team 2006), and its *SPDEP*, *DESIGN* and *GLM* packages (Ihaka and Gentleman 1996).

Results

While surveying for moose over two separate years, from January to March, 2006 and January to March, 2007, a total of 428 10 m × 10 m plots were examined within the study area (Fig. 1). Fresh snow signs (within 24 hours) of moose use were found in 19 plots. Due to the random layout of the survey in each year, the majority of these plots were visited only once. Only a few plots, by coincidence, were near to plots of the past year. When the distance between plots from each of the two years was less than 200-m, we deleted one of them to avoid clustering.

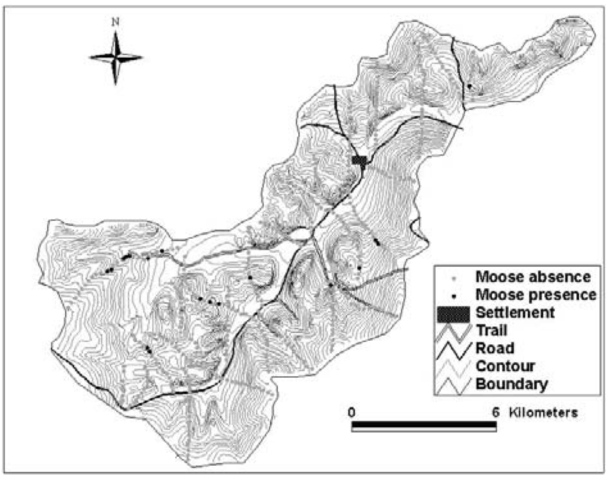

Fig. 1 Distribution of moose across the study area of the Heilongjiang Shengshan Forest farm (over two separate years from January to March, 2006 and January to March, 2007).

Resource selection function models

The top four RSF models were considered for resource and human disturbance variables at multiple scales, respectively, exhibiting significant univariate difference between “use” and “non-use” survey sites.

Table 2. Number of model parameters (k) , AICc Δ and w_i, and Kappa value for the top four logistic regression models for moose in Shengshan Forest Farm (January to March, 2006 and January to March, 2007).

No.	Logistic Model	k	AICc	AICcΔ$_i$	AICc w_i	Kappa value
1	ALT + WET + DROAD [a] + DSETTLE [a] + DSETTLE + DTRAIL [a] + MDB- D + NDVI + OROE + MCB- D	11	135.97	0.00	0.311	0.77
2	ALT + WET + DROAD [a] + DSETTLE [a] + DSETTLE + DTRAIL [a] + MDB- D + NDVI + OROE + MCB- D + LAR-D	12	136.05	0.08	0.298	0.75
3	ALT + WET + DROAD [a] + DSETTLE [a] + DSETTLE + DTRAIL [a] + MDB- P + MDB- D + NDVI + OROE + MCB- D + LAR-D	13	136.53	0.56	0.235	0.721
4	ALT + WET + DROAD [a] + DSETTLE [a] + DSETTLE + DTRAIL [a] + MDB- P + MDB- D + NDVI + OROE + LSS-P + MCB- D + LAR-D	14	137.31	1.34	0.159	0.705

[a]: Squared second term for nonlinear Gaussian function.

Table 3. Coefficients (*β*) and 95% confidence intervals from resource-selection models for moose in Shengshan Forest Farm.

	Logistic regression model	
Covariate	*β*	95% CI
Intercept	-26.244	-46.166－-8.666
ALT	-0.010	-0.025－0.002
WET	-0.058	-0.128－0.006
DROAD [a]	0.088	0.008－0.173
DSETTLE [a]	-0.091	-0.191－-0.009
DSETTLE	1.162	0.147－2.470
DTRAIL [a]	-0.042	-0.098－-0.003
MDB- D	7.870	3.040－13.809
NDVI	31.611	5.305－60.639
OROE	6.312	-2.900－15.287
MCB- D	6.739	2.025－12.363

[a]: the same as table 2.

For the resource selection of moose, the first most parsimonious resource model consisted of nine covariates for vegetation patch density, NDVI, altitude, wetness, occurrence of roe deer, human disturbances and their nonlinear terms for human disturbances (k=11, AICw=0.311); the second most parsimonious resource model incorporated *Larix gmelinii* patch density and had a slightly lower AICw (k = 12, AIC w =0.298) (Table 2). Although the top four logistic models all had predictive capacity (Kappa > 0), the first most parsimonious model has the greatest AIC weight (AIC w =0.311) and the best predictive capacity among them (Kappa = 0.77) (Table 2). Consequently, we selected the first most parsimonious logistic model as our final predictive equation. Moose distribution was positively related to areas with higher densities of mixed deciduous broadleaf patch and mixed coniferous and broad leaf patch, and a higher NDVI value. It was negatively related to altitude and wetness, positively to occurrence of roe deer, for these covariates had confidence intervals that approached 0 (Table 3).

Response of moose to human disturbances

That model contained linear and non-linear terms for distance to human disturbances, which demonstrated a convex relationship with a peak at 6 km from the settlement and odds ratio of moose occurrence of moose remained relative low within 3 km from roads, whereas relative high within 4 km from trails (Fig. 2). Our results showed that moose avoided the disturbance from settlement and roads drastically, but selected the areas near the trails.

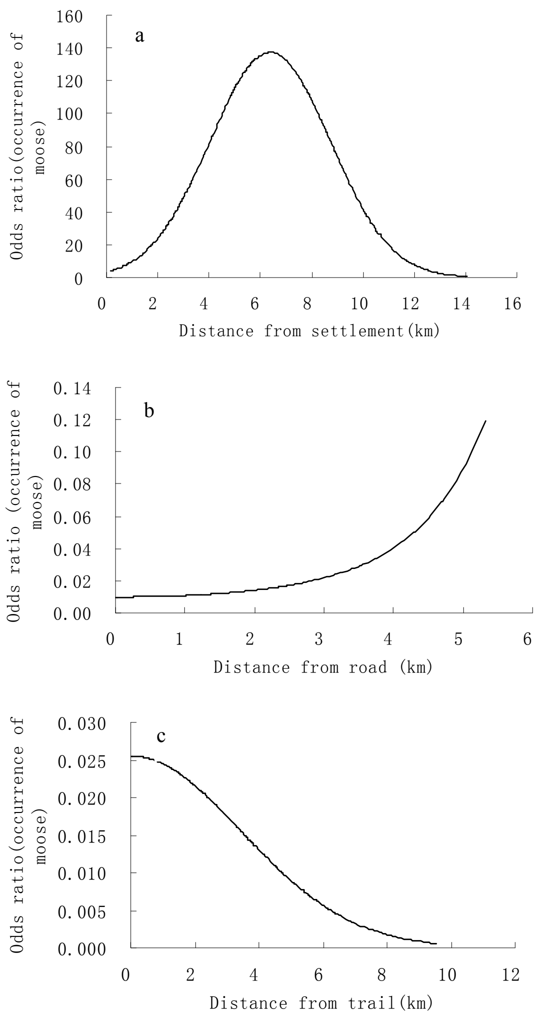

Fig. 2 Plots representing the likelihood of occurrence of moose relative to three types of human disturbance features (a, b and c) found across the study area of the Heilongjiang Shengshan Forest Farm. Animal occurrence was allowed to vary with distance from disturbance features while other covariates were held at their mean values.

Discussion

Scale is an often used, but poorly defined and understood term (Csillag et al. 2000). Scalar principles need to be considered in a context specific manner. When representing scalar processes, one could consider the scale of the phenomenon or the scale of measurement, statistical summary, and modeling (Turner et al. 1989; Dugan et al. 2002). Our study is the first to reveal resource selection and response of moose at patch and landscape scales in northeastern China. Previous studies of moose winter habitat selection in China only conducted at microhabitat or forest stands scales and did not emphasis the influence of more broad-scale and human disturbance on their ecology (Yu et al. 1991, 1993; Zhang, 2001). In this area, our results suggested that moose selected areas with higher densities of mixed deciduous broadleaf patch, mixed coniferous and broad leaf patch, and a higher NDVI value and were disturbed by human beings at landscape scale. This suggests that moose responded to broad-scale elements. This concurs with Maier et al. (2005) who reported that moose, in interior Alaska, tended to occur in areas with large high-density patches of varied habitat and selected heterogeneous habitat. NDVI was our surrogate for vegetation quality and quantity (Cihlar et al. 1991). NDVI is highly correlated with leaf-area index (Cihlar et al. 1991). Annual shoots are the main food for moose during winter (Yu et al. 1993) and food availability is a limiting factor for moose distribution during winter (Dussault et al. 2005), which together mean that there would be an increased use by moose of those forest stands that provide more abundant food (Dussault et al. 2005). The places where NDVI in September was higher would provide more abundant food, in the form of annual deciduous shoots, for moose during winter. During this time, in choosing particular relatively small areas of forest, moose make trade-offs among the available habitat resources to achieve the most favorable energy balance (Daussalt et al. 2005). Consequently, land and forest managers should arrange the logging sites to maintain or create the heterogeneous and abundant food habitat to benefit the survival of moose.

In this study, human disturbance has been revealed to be important factors influencing the distribution of moose populations. However, response of moose to different human disturbance significantly differed. Moose selected area near trails, whereas avoided settlement and roads drastically. Presence of trails showed a significant tendency for moose to be attracted to trails. These trails without human disturbance could serve as convenient travel corridors for moose and could also provide large and easily accessible amounts of forage along their edges. As such, it is understandable that trails within the study area would be utilized rather than avoided by moose (Wisdom and Cook 2000). Avoidance of roads and settlement by moose may lead to the indirect loss or fragmentation of the habitat (Jeager and Fahrig 2004; Jaeger et al. 2005). Similarly study by Jiang et al. (2007) indicated that movement of red deer avoided forest roads from 1.6 km, village from 8.2 km and abandoned roads from 2.2 km. During recent decades, with the rapid development of forest economics, more human settlements and denser road network have been built up in northeastern China. In addition, avoidance responses were greatest for major developments associated with the highest level of human activities and our results approach the maximum of a widely reported threshold distance of 500 m to 5 km from a disturbance (Czech 1991; Nellemann and Cameron 1998; Vistnes and Nellemann 2001; Mahoney and Schaefer 2002; Frid 2003). Thus, human disturbance in this area were seriously impacting spatial distribution of moose populations.

Management implications

The study concludes that moose selected heterogeneous habitat with high-density patches of mixed deciduous broadleaf patch and mixed coniferous and broad leaf stands, and the behavior of avoidance for human disturbance (i.e. settlement and roads) may lead to indirect habitat loss. Hence, land and forest managers should maintain such habitat by adopting suitable forest harvest patterns. They should focus on quality of habitat by restoring and managing the vegetation density and cover. Moreover, they should take measures to mitigate avoidance of moose for village by guiding activities of local people. They can minimize the influence of roads by closing some roads in key habitat, and protect the areas near the trails by controlling human activities disturbances (Millspaugh et al. 1998; Nielsen et al. 2009).

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